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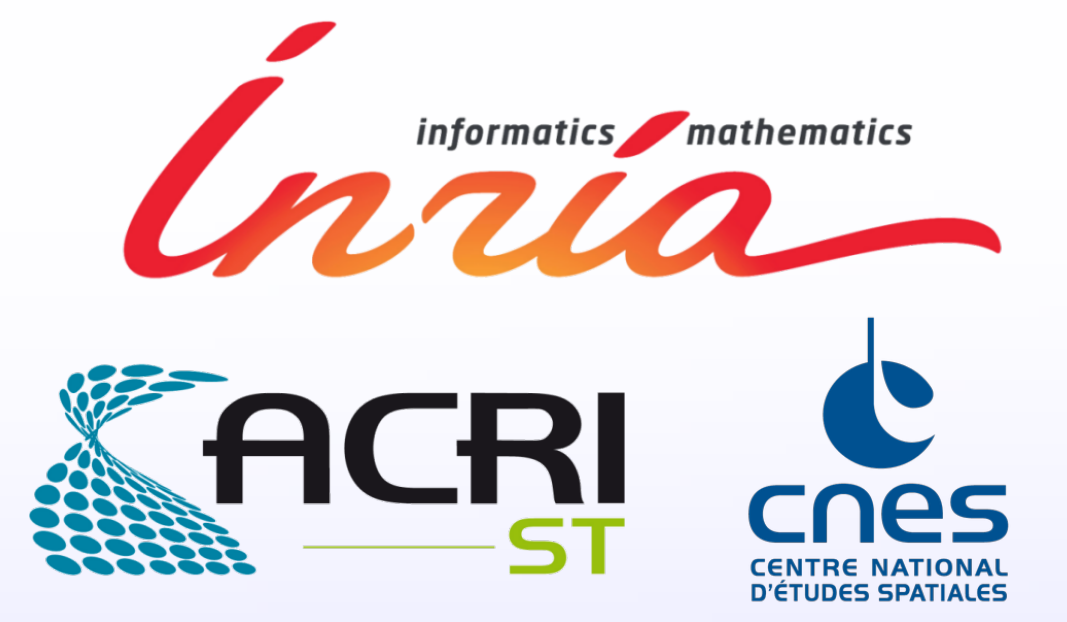
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From Satellite Images to Vector Representations

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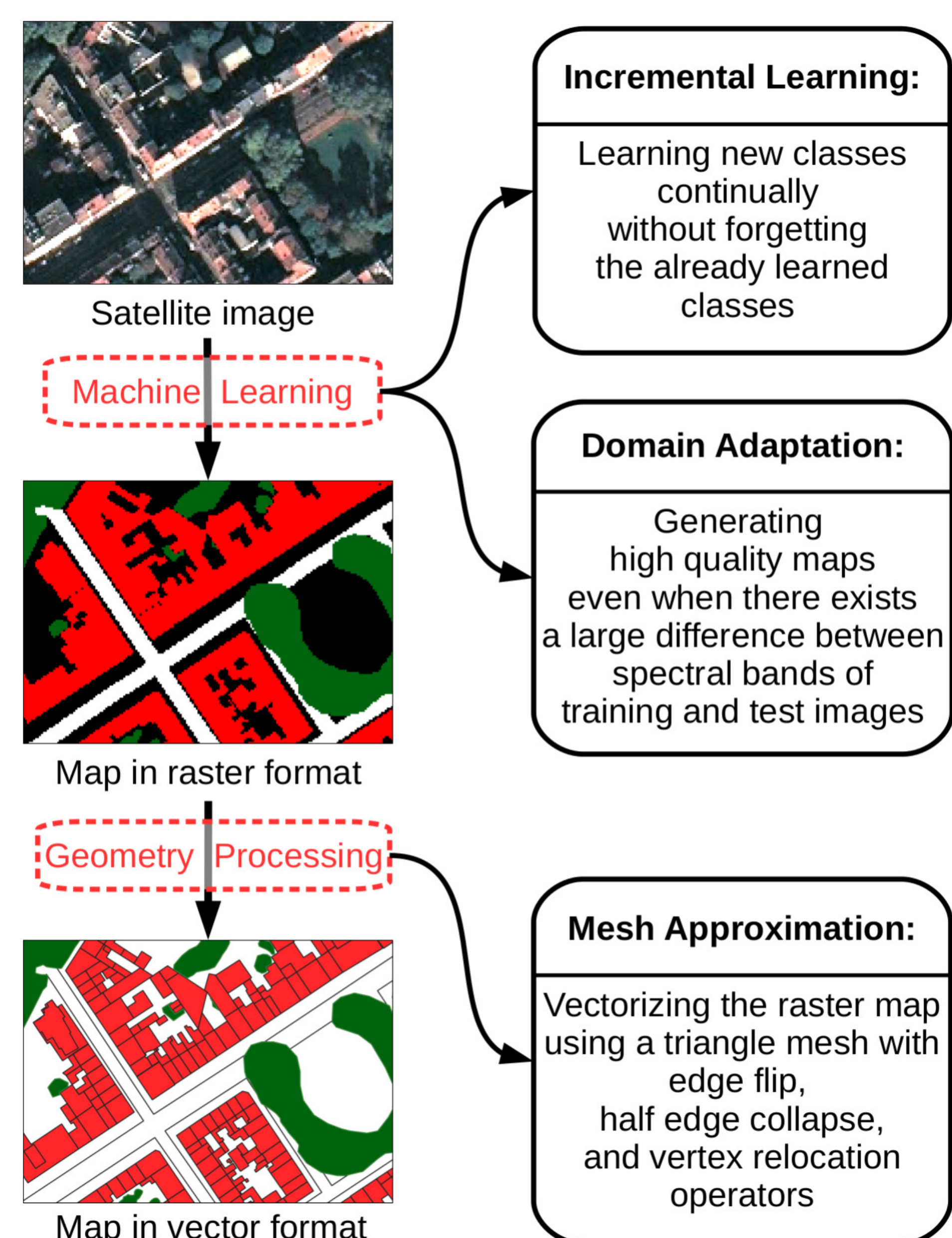
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Introduction

One of the most popular challenges in the field of remote sensing is to generate vector representations from satellite images to be included into various GIS applications. One way to generate the aforementioned vector representations is to split this task into two consecutive sub-tasks, where the first one consists in generating pixel-wise maps in raster format using advanced machine learning techniques, and the second one aims at vectorizing the obtained map by applying computational geometry methods. During my PhD I have worked on various problems in both sub-tasks.

Overview



Conclusions

Incremental Learning: To the best of our knowledge, we proposed the first work on incremental learning for semantic segmentation.

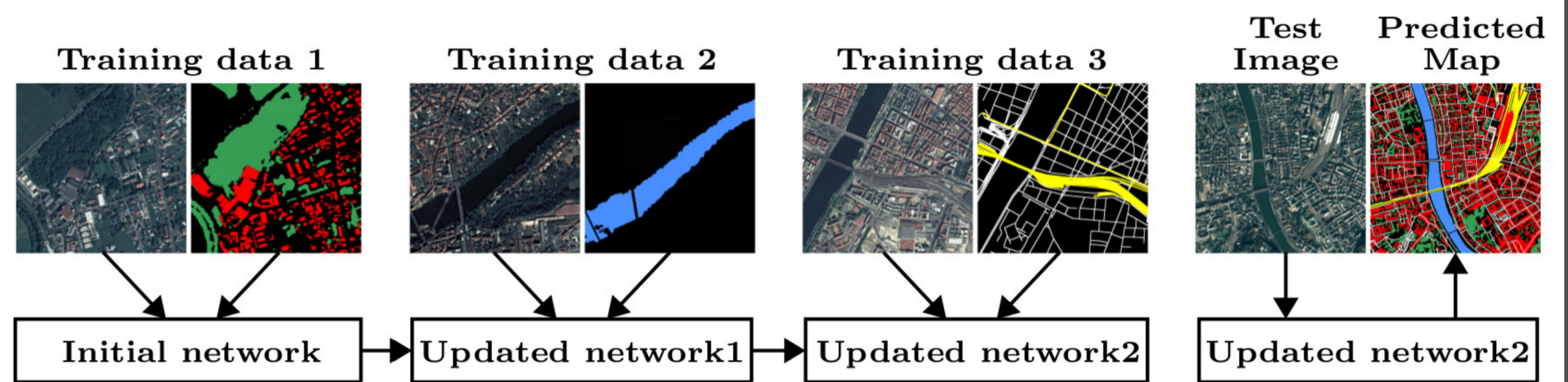
Domain Adaptation: The proposed approach is architecturally simple but powerful. We achieve a better performance than the existing approaches in a much shorter period of time.

Mesh Approximation: The approach yields a better accuracy than the simplification algorithms in common GIS softwares, although our method requires significantly less number of vertices.

References

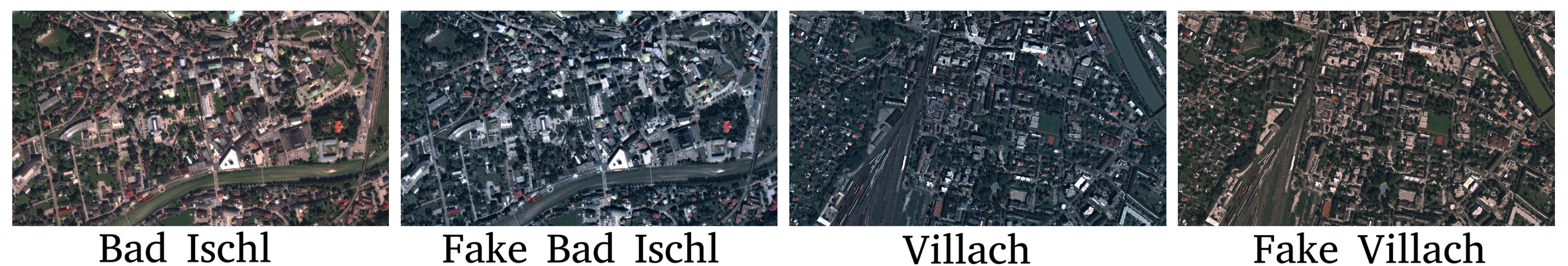
- [1] O. Tasar, Y. Tarabalka, and P. Alliez. Incremental learning for semantic segmentation of large-scale remote sensing data. *IEEE JSTARS*, 2019.
- [2] O. Tasar, SL Happy, Y. Tarabalka, and P. Alliez. Colormapgan: Unsupervised domain adaptation for semantic segmentation using color mapping generative adversarial networks. *ArXiv*, 2019.
- [3] O. Tasar, Y. Tarabalka, and P. Alliez. Continual learning for dense labeling of satellite images. In *IEEE IGARSS*, 2019.
- [4] O. Tasar, E. Maggiori, P. Alliez, and Y. Tarabalka. Polygonization of binary classification maps using mesh approximation with right angle regularity. In *IEEE IGARSS*, 2018.

Incremental Learning

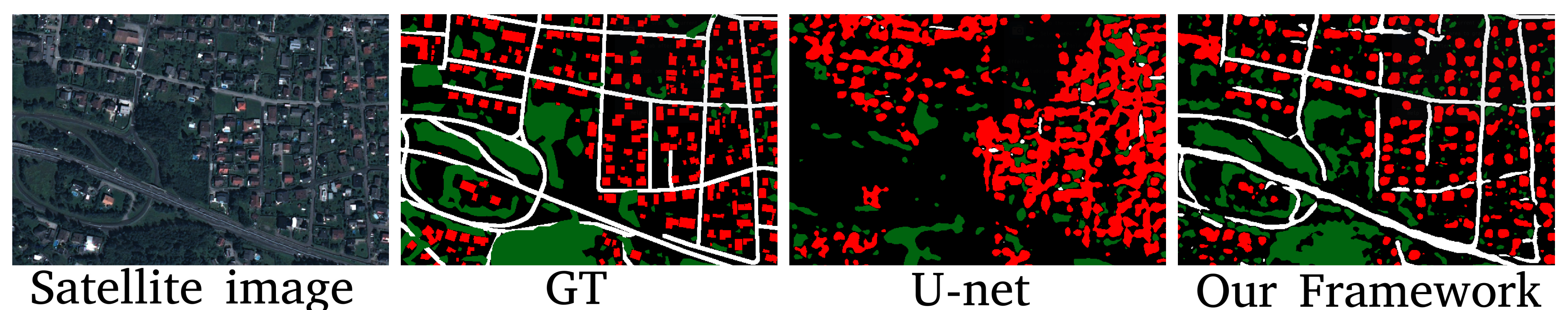


- When new classes are added to the already trained model, the current approaches suffer from catastrophic forgetting (significant performance drop for the previous classes).
- The training phase of our framework [1, 3] has two stages: adaptation and remembering.
- During the adaptation, we use the new ground-truth to learn new classes on the current data.
- We use the output of the previously trained model to fine-tune old classes on the current data.
- In the remembering phase, we store only a small portion of the previous training data, and we use it to remind the network the learned information for old classes from the previous data.

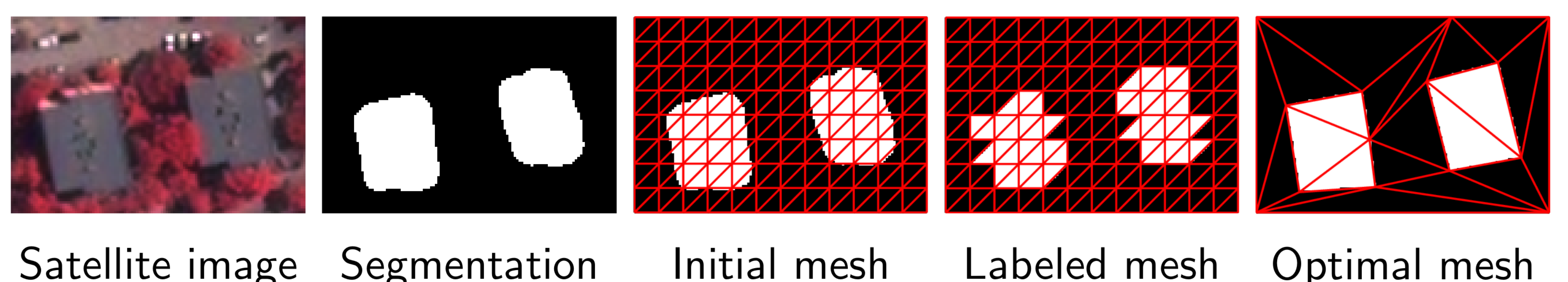
Domain Adaptation



- When there is a large shift between the spectral bands of training and test images, the existing machine learning models fail to segment the test data.
- We generate fake training images that are semantically exactly the same as the original training images, but whose spectral distribution as close as possible to test images by ColorMapGAN [2].
- We then use the fake training data to fine-tune the model trained on the original training data.



Mesh Approximation



- We transform the initial mesh to the optimal mesh by minimizing an objective function with certain operators [4].
- Our objective function balances between fidelity to the classification map in ℓ_1 norm sense, right angle regularity for polygonized buildings, and final mesh complexity.
- The operators: edge flip, half edge collapse, vertex relocation.

